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Study on Thermal Conductivity of Personal Computer Aluminum-Magnesium Alloy Casing

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Abstract

With the rapid development of computer technology, micro-state atoms by simulating the movement of material to analyze the nature of the macro-state have become an important subject. Materials, especially aluminium-magnesium alloy materials, often used in personal computer case, this article puts forward heat conduction model of the material, and numerical methods of heat transfer performance of the material.

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Keywords: aluminum - magnesium alloy; thermal conductivity; personal computer case; computer technology; heat conduction

1. Introduction

There are two main difficulties associated with the widespread use of numerical models. First, the model results do not always agree with the experimental results because of uncertainties in the values of several model input parameters that cannot be estimated from the fundamental principles. It is very difficult to estimate the value of absorption coefficient. However, methods are not very accurate. It is very difficult to calculate the effective values in the presence of a cloud of metal composition. Finally, there may also be uncertainties in thermo-physical properties of the Al-Mg alloys material. Second, the

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numerical heat transfer processes are unidirectional in nature and designed to calculate characteristics from the welding variables. However, the ability to prescribe conditions to attain a particular characteristic is often needed but not currently possible.

These major problems can be solved by combining the numerical models with a suitable optimization algorithm. First, the reliability of the calculated results can be improved by estimating uncertain input parameters from a limited volume of experimental data. By coupling a genetic algorithm (GA) based optimization method [1-4] with a three dimensional (3D) heat transfer model [5, 6], the optimized values of these uncertain parameters can be determined so that the computed weld geometry agrees well with the experimental data. Second, the GA can systematically search for multiple solution sets of welding variables [7-11], each of which can result in a specific weld geometry. Since the search involves a well tested forward heat transfer model, the estimation of uncertain parameters and multiple sets comply with the phenomenological laws.

2. Heat transfer model

A 3D heat transfer model [5, 6] is used for the calculation of temperature fields from a set of specified conditions and materials properties. Since the main goal here was to establish a methodology to estimate uncertain parameters and provide an inverse modeling capability, a simple forward model was selected. Al-Mg alloys were chosen because of its high thermal conductivity because of which convection is not very important. The main assumptions of the model are the following: A constant temperature equal to 100℃ is assumed. The model calculates weld geometry based on several parameters which include material properties, process parameters and geometrical parameters.

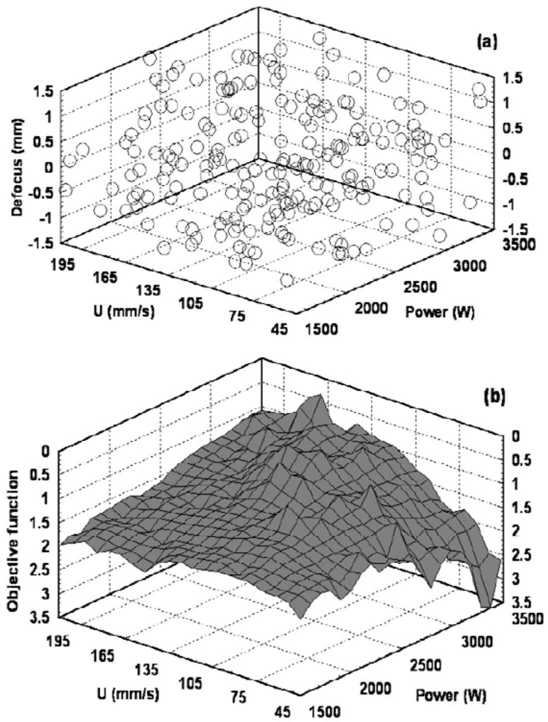

Fig.1 Initial population of randomly chosen values and their objective function values. (a) A large space of variables was searched to find optimum solutions (b) Low values of objective function.

The two-dimensional temperature field in an infinite plate can be calculated considering heat conduction as:

$$T(r,\varphi) = T_a + \frac{P'}{2\pi\lambda} K_0(\Omega r) e^{-\Omega r \cos\varphi} \tag{1}$$

where (r, φ) designates the location in the plate with the line source as the origin, T_a is the ambient temperature, P' is the power per unit depth, λ is the thermal conductivity, K_0 is the solution of the second kind and zero-order modified Bessel function and, where $\Omega = 1/2k$,and k is the thermal diffusivity.

The radial heat flux conducted I_c can be obtained from the relation:

$$I_c(r,\varphi) = -\lambda \frac{\partial T(r,\varphi)}{\partial r} \tag{2}$$

The model solves these equations to calculate the temperature distribution in the work-piece from the top surface of the sample up to the bottom part. To calculate the temperature profile and hence to calculate the total depth, the model is combined to another computer code which solves the following heat conduction equation:

$$\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} - \frac{1}{k}\frac{\partial T}{\partial x} = 0 \tag{3}$$

Here k is the thermal diffusivity of the work-piece. The other boundary conditions are as follows: The boundary condition for the bottom surface is given by:

$$J(x,y,z)\big|_{z=\max} = h[T_a - T(x,y,z)\big|_{z=\max}] \tag{4}$$

Where $J(x,y,z)$ is the heat flux, h is the heat transfer coefficient, T_a is the ambient temperature, and $T(x,y,z)$ is the local temperature. The temperatures at the surfaces far from the heat source are assumed to be equal to the ambient temperature. The 3D numerical model for the solution of the above equations, henceforth referred to as the forward numerical model, gives the temperature distribution in the work-piece.

The first step in the computational procedure is to optimize the values of the uncertain parameters in the model. Two values of width have been specified for the weld pool cross-section, i.e. at the top and at the bottom of the work-piece to ensure a better correspondence between a low objective function and a good agreement between the calculated and the experimental. The values of absorption coefficient are also randomly generated within an upper and a lower limit. A systematic global search is then undertaken by the GA to find the set of uncertain parameters which result in least value of the objective function, the effectiveness of the search for optimized values of the two parameters is enhanced by using dimensionless values of radius which is comparable in magnitude with the absorption coefficient. The sets of unknown input parameters commonly referred as population in GA, changes with every iteration following the rules of GA. The GA used in the present study is a parent-centric recombination (PCX) operator-based generalized generation gap (G3) model. This particular GA was chosen because it has a faster convergence rate on standard test functions compared to other evolutionary algorithms.

3. Results and Discussion

Since the model is based on well-tested equations of heat transfer the mismatch between the computed and the experimental results may be attributed primarily to uncertainties in some of the input parameters. Values of the absorption coefficient are identified as the important uncertain parameters and their values were estimated from a limited volume of experimental data. Assuming that energy absorption is due to photon-electron interaction, the absorption coefficient for clean flat surfaces can be estimated from the following relation [12]:

$$\alpha = 0.365\left(\frac{\rho}{\lambda}\right)^{1/2} - 0.0667\left(\frac{\rho}{\lambda}\right) + 0.006\left(\frac{\rho}{\lambda}\right)^{3/2} \tag{5}$$

Where ρ is the electrical resistivity (ohm-cm) of the liquid metal at the boiling point, the estimated absorption coefficient may differ from the actual value. Significant errors may also exist in the measured value.

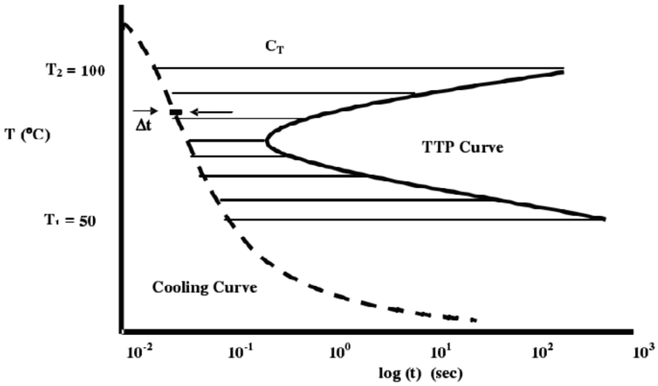

Fig.2 Cooling Curve and TTP Curve Analysis

The dashed line represents the temperature of the alloy as a function of time and the corresponding TTP Curve is seen to its right. The Δt value is taken as the time interval in which data points are collected. The quench factor is proportional to the heat removal characteristics of the quenchant as depicted in the cooling curve for the quenching process.

4. Conclusion

Values of certain parameters like absorption coefficient are often not known accurately. Therefore, a real number based GA was combined with a 3D heat transfer model to estimate the values of these parameters by minimizing the difference between the calculated and the measured Al-Mg alloys conditions. Using these values the computed geometries were found to be in good agreement with the experimentally observed. Numerical models of heat transfer can thus be combined with a GA and a limited volume of experimental data. Even though only two uncertain parameters were optimized using GA in this work, other parameters like effective thermal conductivity and viscosity in a turbulent weld pool and effective values of temperature dependent thermo-physical properties can also be optimized using this methodology.

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